



Intelligent Proactive Maintenance Based on an Optimized Fuzzy Logic Model for Machine State Diagnosis

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Abstract—*Failure Mode and Effect Critical Analysis (FMECA)* method traditionally attempt to identify potential modes and treat failures before they occur based on experts' evaluation. However, this method is extremely cost-intensive in terms of failure mode since it evaluates each failure mode. Moreover, this method is not able to properly treat uncertainty during logical reasoning as it is based on subjective expert judgments and requires a lot of information. Previous studies propose several versions of Fuzzy logic but have not explicitly focused on the combinatorial complexity nor justified the choice of membership function in Fuzzy logic modeling. In this research, we develop an optimization-based approach-referred to *Integrating Truth Table and Fuzzy Logic Model (ITTFLM)*-generates smartly fuzzy logic rules using Truth Tables. This approach allows generating quickly and smartly fuzzy rules by assuring consistency and non-redundancy through logical evaluation. We propose to implement ITTFLM for three types of membership functions (Triangular, Trapezoidal, and Gaussian) to choose the best function that fits our real data. The ITTFLM was tested on fan data collected in real time from plant machinery. The experimental evaluation demonstrates that our model identifies the failure states with more accurate results and can deal with large numbers of rules and thus meets the real-time constraints that impact usually user experience. Future research is expected to expand the size of data in terms of metrics and compare it with other models.

Index Terms—FMECA, Fuzzy Logic, Truth Table, Combinatorial Complexity, Real-time, Industrial fan motor, Knowledge, Data, Artificial Intelligence.

I. INTRODUCTION

For manufacturing sectors, waste reduction, equipment availability improvement, and product quality optimization are three critical metrics to measure performance [1] to stay competitive in the markets. Given that such industrial machines' structure that integrates different components and complex subsystems can often fail, it has a substantial impact on their availability and, as a result, the productivity of manufacturing plants and their performance [2] subsequently generating economic loss and safety issues [3]. In fact, maintenance costs are very expensive, it can cost a major part of the total production costs, which can vary from 15% to 60 % of the cost of goods produced [4]. In order to reach this goal, good practice of maintenance is required. Basically, maintenance is performed in two ways, by repairing the machine when failure has occurred, or by preventing the failure before it happens [5]. The latter is known as proactive maintenance which attempts in addition to identify root causes [6]. On the one hand, the advancement of technologies has encouraged industries to incorporate Artificial Intelligence (AI) techniques

in PHM (Prognostics and Health Management), which aims to monitor, diagnose, and prognostic the health status of industrial equipment [7]. Diagnostics is dealing with fault detection, isolation, and identification when it occurs. Fault detection is indicating if something is malfunctioning in the monitored system, and fault isolation locates the faulty component, while fault identification is the determination of the fault nature when it is detected [8]. On the other hand, a large body of research in the literature exists for both diagnostics and prognostics. However, many diagnosis approaches stop at the fault isolation step, and seldom perform fault identification; and most prognostic approaches assume some diagnosis has been performed and focus on the prognosis of a single failure mode. Moreover, none of these studies provides a complete framework (from data-driven diagnostic to maintenance decision passing by prognostic). To fill the gap in the literature, this paper presents a part of a project that aims to propose a completely optimized proactive maintenance framework from diagnostic to maintenance decisions passing through prognostic. The idea is to exploit information from each previous step. For example, the prognostic step is done for machines that were diagnosed as a failure, then it is done for each failure mode identified at the diagnostic step. We start then by optimizing the diagnostic step, which is the scope of this paper as described in the figure 1.

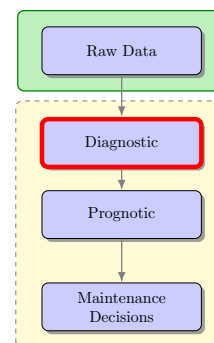


Fig. 1. PHM in a yellow rectangle. The scope of this paper, which is a diagnostic step, is framed in red color.

Failure Mode and Effect Critical Analysis (FMECA) is a diagnostic knowledge-based model that was originally developed by the U.S military and attempts to identify potential modes and treat failures before they occur based on experts'

evaluation. This evaluation is done for each failure mode [9], which is time-consuming. Furthermore, this method is characterized by the inability to deal with uncertain failure data including subjective expert judgments and require data. Thus, Fuzzy Logic (FL), a technique of AI, was developed based on Fuzzy theory since it can work in the absence of data and attempts to model and manipulate imprecise and subjective knowledge imitating human reasoning [10]. FL can be used as a knowledge model or hybrid model when data are available. The use of FL-based diagnostic in literature can be classified into two groups. The first group focuses on FMECA combined with FL based on the assumptions of data certainty. The second group address using FL to replace FMECA but there is no scientific approach to select input members or generate rules as it generates manually and subjectively by listing all fuzzy rules. However, none of the two groups addresses the question of combinatorial complexity. Therefore, there are seldom investigations about taking into consideration the combinatorial complexity while generating fuzzy rules in previous research and practice. Actually, the number of generated rules in the worst case corresponds to all combinations of fuzzy sets. Let's assume, 2 input variables and 1 output variable with respectively (n, m, k) fuzzy sets, then there is $n \times m \times k$, it is the Cartesian product of fuzzy sets of all variables. To the best of our knowledge, this is the first study focusing on studying the way of generating and evaluating the truth of rules to deal with time-consuming.

In this paper, we contribute to the literature by developing an optimization framework to generate automatically and quickly fuzzy rules. The proposed modeling framework-refereed to as *Integrating Truth Table and Fuzzy Logic Model (ITTFLM)*-generates smartly fuzzy logic rules using Truth Tables. This approach allows diagnosing the machine state by combining the two distinct traditions in information engineering: data-driven modeling and knowledge representation. the methodology is based, on one hand, on data extracted from sensors, on the other hand, the FMECA of machine state is selected as the knowledge source, to validate our model on real data.

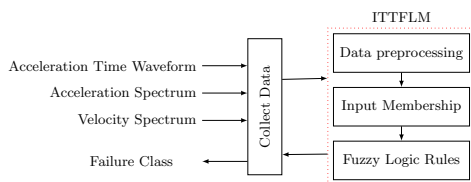


Fig. 2. Three main contributions with a list of inputs and output.

In the light of above mentioned short comments on the aims of the study, the contributions may be shortened as follows (see Figure 2):

- 1) A new reduction method to specify fuzzy sets of input memberships
- 2) A simulation method to demonstrate the choice of membership function

- 3) ITTFLM is designed to automatize FMECA processes based on Vibration data
- 4) Generating rules in ITTFLM are based on Truth Table.

The remainder of this paper is organized as follows. In section 2, we review the relevant academic literature. Section 3 describes the model formulation. Section 4 is dedicated to our experiments. Finally, in section 5 we conclude the paper and outline directions for future research

II. RELATED WORK

This section first reviews the literature on maintenance strategies. Second, it reviews the FMECA model. Finally, it reviews relevant contributions in the field of the fuzzy logic model as a background for the development of our optimization model.

a) *Maintenance strategies:* With the development of reliability engineering in the 1950s, the concept of preventive maintenance, and time-based maintenance (TBM) was introduced [11]. TBM was based on the well-known "bathtub curve", which represents the increase in the failure rate of products over a certain period of operation. In the 1970s, the development of machine diagnostic techniques brought the concept of condition-based maintenance (CBM), in which preventive actions are carried out depending on the detected symptoms of failure [11]. However, The various maintenance strategies deployed by manufacturers are continuously evolving, given the increasing complexity of manufacturing processes and equipment. Depending on the complexity of the machine and the impact of an unexpected failure on that machine, Manufacturers select the most appropriate maintenance strategy to maintain their asset base [1] or even use a combination of reactive maintenance (RM), preventive maintenance (PM), predictive maintenance (PdM) and proactive maintenance (PaM). Although there is a huge interest in integrating the PdM method in diverse industries, the principal disadvantage in the selection of this policy is that it's too expensive, complex [12], and obtaining an accurate and reliable Remaining Useful Life (RUL) prediction of equipment is difficult [13]. For example, [14] proposed a new PdM framework, based on prognostics information, that allows providing reasonable decisions to avoid system failure, maximizing the system lifetime, and reducing the inventory cost. Most industries are still adopting preventive maintenance, For example, [15] presents a study concludes that the most preferred proactive maintenance strategy for the case study was preventive maintenance, followed by reliability-based maintenance while predictive maintenance is the least preferred maintenance strategy in the rolling mill industry. The concept of maintenance has significantly evolved, owing to important contributions in both research and industry area. In the literature, reactive and proactive maintenance are the two maintenance strategies described [16]. *Reactive strategy:* also called corrective maintenance, unplanned maintenance, or run-to-failure maintenance, it is considered the oldest maintenance strategy, it is based on "fix it when it's broken", which means that it is performed only after a failure occurs [17]. The

effects of reactive strategy contribute to high costs. *Proactive Strategy*: aims to prevent failures by taking action before a failure of a machine occurs [18], in order to reduce costs [19], it differs in preventive and predictive maintenance [20]. *Preventive maintenance* is planned and scheduled maintenance, it involves periodic maintenance of the system to prevent it from breakdowns and failures [21]. While *Predictive maintenance* uses advanced analytics based on the asset's actual operating conditions to forecast the future failure which allows maintenance to be planned before the failure occurs [22].

b) *FMECA*: One of the main reliability analysis methods used to determine maintenance action priority is *Failure Mode and Effect Critical Analysis* (FMECA). It is developed and applied by NASA in the 1960s to improve and verify the reliability of space program hardware in Apollo program [23]. This technique is used at diverse steps in the product life cycle in several fields, such as medical, nuclear, aerospace, and other manufacturing industries [6]. The FMECA method aims to identify potential modes and treat failures before they occur, intending to eliminate them or minimize the associated risks. It consists of systematically considering, one after the other, each component of the system studied and analyzing the causes and effects of their potential failures. Each highlighted failure is then analyzed to determine its occurrence, severity, and detectability. The multiplication of these three values allows calculating the criticality index, which is called the Risk Priority Number (RPN) [24]. Many authors consider FMECA and the development of risk analyses as an essential part of maintenance management strategies [25]. [26] used the FMECA approach to determine the critical equipment in a super thermal power plant. In the military sector, it has been applied for missile equipment maintenance decisions, where it improves the work efficiency and relevance of maintenance, and avoids excessive maintenance [27]. [28] applied to analyze the reliability of metro door system. Despite its wide use, FMECA is a problem for three main reasons [29]: (i) the subjectivity of experts' judgments to determine the three criteria of RPN. (ii) the inability to deal with uncertain failure data. (iii) the absence of scientific basis in the RPN calculation formula, and many duplicates in RPN results. To overcome these limitations, researchers have proposed models based on Fuzzy logic.

c) *Fuzzy Logic*: This model was applied in many areas in particular in maintenance and has achieved impressive results. In the literature, we distinguish two types of using fuzzy logic in diagnostic: integrated fuzzy logic in FMECA to calculate RPN and using fuzzy logic on vibration data in the absence of experts. [2] proposed a model in maintenance decision-making support for textile machines using vibration monitoring and vibration spectrum [10]. It allows also the utility operators to achieve more precise outage predictions and optimize the real-time operation and maintenance schedule in weather risk analysis in distribution outage management [30], and for scheduling predictive maintenance on communication networks [31]. FL proved that it is an appropriate tool also in the maintenance strategy selection approach to select the best

maintenance strategy for a rolling mill factory [15]. The neuro-fuzzy tool ANFIS is used to evaluate the performance loss of the system according to the degradation of components and the deviations of system input flows integrating knowledge from two different sources: expertise and real data [32]. It has also worked out on the gap between the two distinct traditions in information engineering: knowledge representation and data-driven modeling [33]. However, using Fuzzy logic to diagnose machines based on vibration data in maintenance applications has some limitations. On the one hand, there is no method to define input members. Most researchers used triangular functions without justifying this choice. On the other hand, rules are generated manually and no algorithm guarantees the consistencies and non-redundancies of rules concerning time complexity.

All this literature constitutes essential background and methodological foundation on which we build to implement a descriptive model for diagnostic machines using vibration data. In this respect, we propose in this paper an intelligent and fast modeling framework (ITTFML) that explicitly generates rules based on truth tables. The choice of membership functions is done by the simulation method.

III. FUZZY MODELING

In this section, we present the framework of the proposed Model (ITTFML). To overcome the limitations previously explained, a new methodology is developed based on the Fuzzy Logic Models and Truth Table method to simplify rules generation. Fuzzy Logic consists of four steps as mentioned in Figure 3.

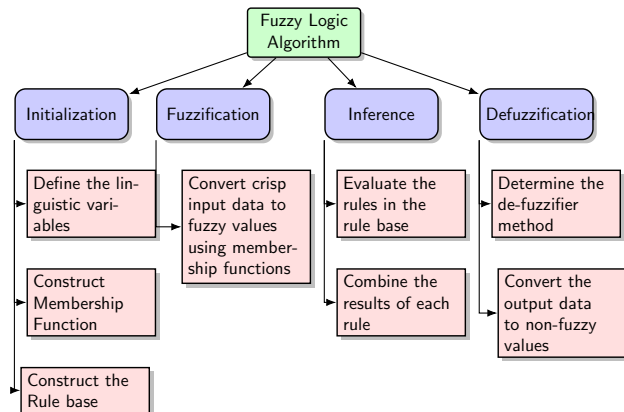


Fig. 3. Steps of Fuzzy Logic Algorithm.

We present then our proposed modeling related to the three blocks of the initialization step: As a tableII, the data used is containing 160000 observations for each variable every 4 hours, during approximately 170 days for each one of the four sensors, and FMECA results are saved at the same time. this caused us issues with calculation time and costs. Integrating the Fuzzy Logic Model allows us to overcome this issue, we grouped the data by Machine State Class, then we took each class and we determined an interval by taking the minimum

value and the maximum value of the data array. The following algorithms give a simple way how to identify the Min and Max values of each array:

Algorithm 1 Data reduction - Intervals definition

```

1: for  $i = 0$  to array length - 1 do
2:   for each element in the array do
3:     Set Max to array[i]
4:     Set Min to array[i]
5:     if array[i]  $\geq$  Max then
6:       Set Max to array[i]
7:     else
8:       if array[i]  $\leq$  Min then
9:         Set Min to array[i]
10:      end if
11:    end if
12:  end for
13: end for

```

The linguistic variables correspond to the state of machines. After defining of intervals (membership functions), we checked each interval if it includes other intervals, the following algorithm gives a simple way how to check the inclusion between intervals:

Algorithm 2 Intervals inclusion detection

```

for  $i = 0$  to arr1 length - 1 do
2:   for  $j = 0$  to arr2 length - 1 do
3:     for each element in the arr1 do
4:       if arr1[0]  $\geq$  arr2[0] and arr1[length - 1]  $\geq$ 
arr2[length - 1] then
5:         Replace arr2 with arr1
6:       end if
7:     end for
8:   end for
9: end for

```

Intervals inclusion can help with optimizing FL rules. Given that we are aiming to generate more than only one output, our model can generate possible machine states in real-time, and let the decision-making step for the agents, this will minimize time, costs, and resources. Moreover, it is an important factor to not eliminate the human factor, but it will be a collaboration between Human and machine capabilities. In our algorithm, each rule is generated as a combination of the degree of each input and output variable at each step. Each row of the truth table represents a rule of Fuzzy Inference, it contains one possible configuration of the input and output variables in the table according to linguistic terms defined for each variable, which are machine state. The idea is to optimize the generation process by ensuring complete and fast fuzzy rules based on logical evaluation rather than the linguistic rule. To the best of the authors' knowledge, this is the initial attempt that merges Truth Tables and FL as performed in this study.

IV. EXPERIMENTS

A. Data Collection

1) *Data Acquisition*: The process of collecting and storing data from a physical process in a system is known as data acquisition [3], it has become more affordable and achievable due to the fast progress of data acquisition technology [8]. There is a huge variety of signals such as vibrations, oil analysis, temperature, acoustics, and pressure. To collect these data, many sensors have been developed such as ultrasonic sensors, accelerometers, gyroscopes, rain sensors, etc. Nowadays technologies provide ways to improve sensors and computers, which implies an easier way of storing data.

2) *Data processing*: The acquired data may contain some inconsistent, missing, or noisy values. Given that quality of the data has a significant impact on the results achieved. Therefore, preprocessing approaches can be applied to improve these results. It can be considered one of the most critical processes, which deals with the preparation and transformation of the original data. Data preparation techniques can be classified into three grades:

a) *Data Cleaning*: Data manipulation (filtering, transforming, removing noise) is necessary before using the data for any purpose, in fact, these data are usually noisy, incomplete, or inconsistent, especially the manually entered data, and in general, many factors including human factors can cause these errors. To improve data quality, it is necessary to detect and remove these errors [34]. There is no simple way of cleaning. Some techniques are based on human observation and inspection. Using the mean or median values to fill unknown values with zeros. Moreover, many other methods such as regression techniques can be used for missing values estimating [35].

b) *Data Transformation*: Data transformation provides a more appropriate form of data for the next step in the modeling phase. It can include normalization, which involves scaling data to a narrow range to make different signals comparable. Also, smoothing techniques are used to separate the signal from the noise in the data. [36] gives a short overview of different smoothing methods.

P ¹	g ²	fft ³	fftg ⁴	MSC ⁵	FCC ⁶
P1-P2	Data	Data	Data	Normal	Normal
P3-P4	Data	Data	Data	Imbalance	Rotor
P1-P2	Data	Data	Data	Structural fault	Frame
P3-P4	Data	Data	Data	Misalignment	Link
P1-P2	Data	Data	Data	Mechanical looseness	Looseness
P3-P4	Data	Data	Data	Bearing lubrication	Lubrication fault
P1-P2	Data	Data	Data	Gear fault	Gear
P3-P4	Data	Data	Data		

¹ Sensor position; ² Acceleration time waveform; ³ Velocity spectrum. ⁴ Acceleration spectrum; ⁵ Machine State Class; ⁶ Failure Cause Class.

TABLE I

FAILURE CLASS GENERATED BY FMECA

c) *Data Reduction*: A large volume of data might be an issue for machine decision-making due to the high com-

putational cost. As the amount of data rises, so will the time spent by the hardware. Some approaches have been developed to overcome this issue and maintain the computing cost low while keeping the volume of data sufficient. The most well-known is principal component analysis [37]. Other data reduction methods are proposed in [38], [39], [40] and [41]. The data used are numerical data uploaded from sensors, attached to the results of the FMECA method including Failure nature and cause, done by experts manually every four hours, corresponding to vibration and velocity data, collected during approximately 170 days. There are 7 failure cause classes corresponding to seven failure classes generated by applying FMECA manually by experts every 4 hours.

Given that The Root Mean Square (RMS) value of velocity is one of the important factors for machinery status diagnosis, we calculate the RMS of $fftv$ and $fftg$ in each sensor position for each machine state class identified by the FMECA method using the following formula:

$$x_{RMS} = \sqrt{\frac{1}{n} (x_1^2 + x_2^2 + \dots + x_n^2)}$$

We started by grouping the data we have by machine state class, which gave us a lot of data corresponding to each state, then we selected only the minimum value X_{min} and the maximum X_{max} of each variable $fftv$ and $fftg$, which allows us to create intervals $Iv = [Xv_{min}, Xv_{max}]$, and $Ig = [Xg_{min}, Xg_{max}]$ for each machine state as follows: To better

$fftv^1$	$fftg^2$	MSC ³	FCC ⁴
Iv_1	Ig_1	Normal	Normal
Iv_2	Ig_2	Imbalance	Rotor
Iv_3	Ig_3	Structural fault	Frame
Iv_4	Ig_4	Misalignment	Link
Iv_5	Ig_5	Mechanical looseness	Looseness
Iv_6	Ig_6	Bearing lubrication fault	Lubrication fault
Iv_7	Ig_7	Gear fault	Gear

¹ Velocity spectrum; ² Acceleration spectrum.
³ Machine State Class; ⁴ Failure Cause Class.

TABLE II
FAILURE CLASS OF EACH INTERVAL

illustrate the results of the data reduction method. We plot it as a histogram. Figure 4 analyzes the relation between the intervals of Iv and MSC (Machine State Class). The green color corresponds to the minimum RMS of $fftv$ while the purple color is the maximum.

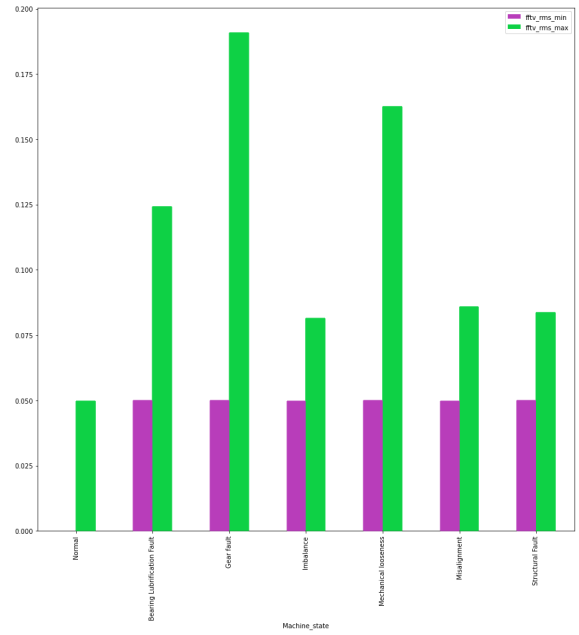


Fig. 4. MSC representation according to RMS measure of $fftv$ when generating Iv intervals.

Respectively, the figure 5 represents Ig for the metric $fftg$

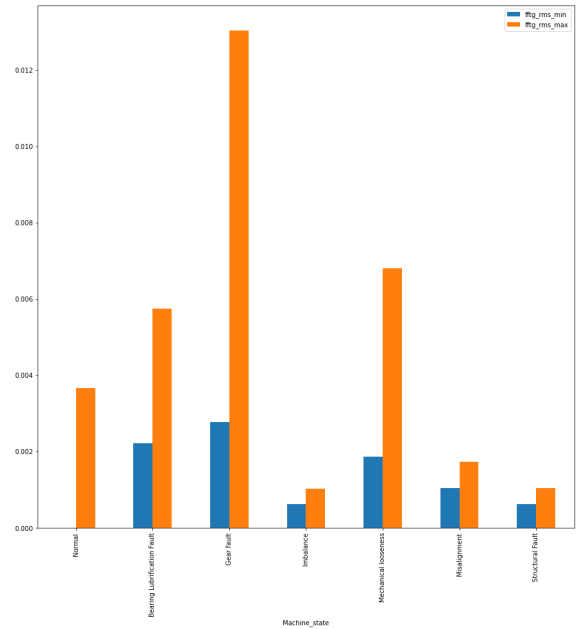


Fig. 5. MSC representation according to RMS measure of $fftg$ when generating Ig intervals.

The machine state depends on the evolution of Xv and Xg in the intervals Iv and Ig . Applying the truth table for the two inputs variables using **Logical conjunction** gave us $n = 2^7$ results, only 7 are possible, the table follows shows the possible results :

fftv ¹	fftg ²	Nr ³	Im ⁴	St ⁵	Mi ⁶	MI ⁷	BI ⁸	Gf ⁹
Iv1	Ig1	1	0	0	0	0	0	0
Iv2	Ig2	0	1	0	0	0	0	0
Iv3	Ig3	0	0	1	0	0	0	0
Iv4	Ig4	0	0	0	1	0	0	0
Iv5	Ig5	0	0	0	0	1	0	0
Iv6	Ig6	0	0	0	0	0	1	0
Iv7	Ig7	0	0	0	0	0	0	1

¹ Velocity spectrum; ² Acceleration spectrum; ³ Normal state.
⁴ Imbalance; ⁵ Structural fault; ⁶ Misalignment.
⁷ Mechanical looseness; ⁸ Imbalance; ⁹ Gear fault.

TABLE III
TRUTH TABLE FOR POSSIBLE MACHINE STATE USING LOGICAL CONJUNCTION

Noting that after analyzing the figures 4 and 5, as well as the data in the tableIII, we noticed some inclusions and intersections between intervals, considering only the inclusions for the moments, it's defiantly can help with Fuzzy logic rules optimization, which is a more logical and practical solution to adopt, in results we obtain represented in table V.

Our experiment protocol aims to answer the following questions:

- 1) Can the inclusions and intersections impact the outputs of the fuzzy logic controller?
- 2) How can we generate optimized fuzzy logic rules intelligently?
- 3) Which one of the Fuzzy logic sets is the best for our case?

fftv ¹	fftg ²	Nr ³	Im ⁴	St ⁵	Mi ⁶	MI ⁷	BI ⁸	Gf ⁹
Iv1	Ig1	1	0	0	0	0	0	0
Iv2	Ig1	0	1	0	0	0	0	0
Iv4	Ig1	0	0	1	1	0	0	0
Iv5	Ig5	0	0	0	0	0	0	1
Iv7	Ig5	0	0	0	0	1	1	0

¹ Velocity spectrum; ² Acceleration spectrum; ³ Normal state.
⁴ Imbalance; ⁵ Structural fault; ⁶ Misalignment.
⁷ Mechanical looseness; ⁸ Imbalance; ⁹ Gear fault.

TABLE IV
OPTIMIZED TRUTH TABLE FOR EACH MACHINE STATE

B. Fuzzy Logic Controller

1) *Input membership function*: Table helped V in integrating linguistic terms in the identification of the inputs memberships (*Fuzzification*), for each system, the output of the systems are represented in figure 6 three fuzzy decision systems were built, using the trapezoidal, triangular, and Gaussian membership functions for the input linguistic variables Xv and Xg.

2) *Fuzzy Rules*: The fuzzy rules base consisted of 7 optimized rules based on table V, as follows:

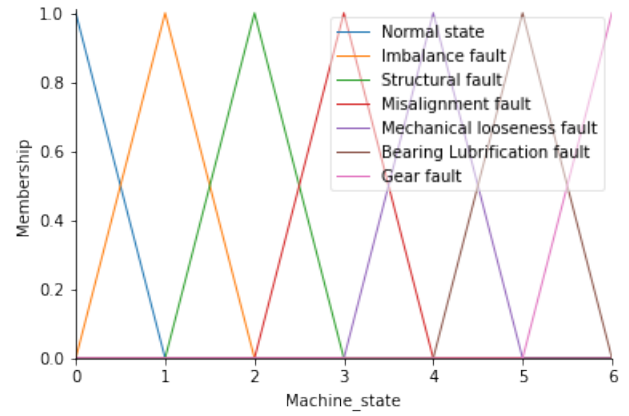


Fig. 6. The output linguistic variable - Defuzzification.

rule	Iv ¹	Ig ²	MSC ³
1	if Iv ₁ and Ig ₁	then	Normal state
2	if Iv ₂ and Ig ₁	then	Imbalance fault
3	if Iv ₄ and Ig ₁	then	Structural Fault
4	if Iv ₄ and Ig ₁	then	Misalignment fault
5	if Iv ₅ and Ig ₅	then	Mechanical looseness fault
6	if Iv ₇ and Ig ₅	then	Bearing Lubrication fault
7	if Iv ₇ and Ig ₅	then	Gear fault

¹ Intervals of fftv; ² Intervals of fftg; ³ Machine State Class.

TABLE V
FUZZY LOGIC RULES

3) *Results*: We ran three experiments in order to compare the three types of FL sets, the triangular membership functions (triMF), Gaussian membership functions (gaussMF), and trapezoidal membership functions (trapMF). We sat two variables from each interval, one is near the minimum value, and the other is near the maximum value of each interval. v_{min} for the minimum value of one of Iv's intervals, v_{max} for the maximum value of one of Iv's intervals, g_{min} for the minimum value of one of Ig's intervals, g_{max} for the maximum value of one of Ig's intervals. The following figures represent some output examples of the three fuzzy logic systems:

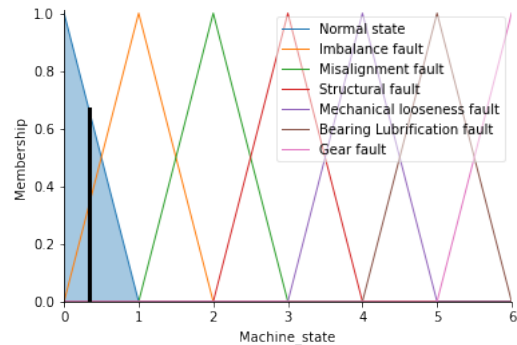


Fig. 7. trapMF - Normal state output.

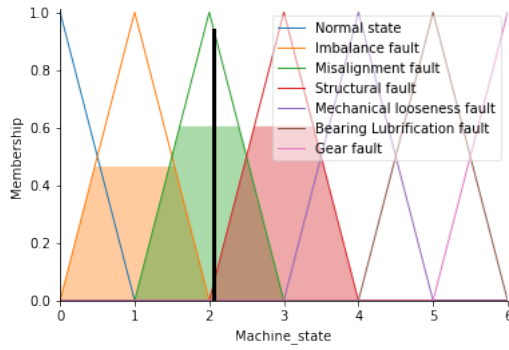


Fig. 8. triMF - Imbalance fault output.

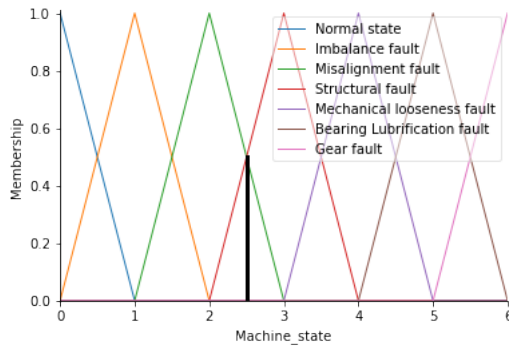


Fig. 9. GaussMF - Structural fault output.

The obtained results are represented in Table VI where E_{XC} corresponds to Excellent and A_{ve} to Average.

C. Discussion

For the Gaussian membership functions (gaussMF), it couldn't generate many outputs, while the other results show a lack of accuracy in the identification of the machine state, this might be due to the nature of the data we have and the fact that the input values are not connected which make the system is too sparse. Note that in some cases it could identify some states with average accuracy. The triangular membership functions (triMF), could identify with good accuracy many machine states, and with poor accuracy in others, this is because this type of fuzzy logic set is considering the median of the value as the point where a state is 100% exist, while the values we choose are near the borders of each interval, mentioning that a value of each state could be anywhere between the borders, not necessarily in the middle. Therefore, the trapezoidal membership functions (trapMF) gave better results, and better accuracy, in some cases we considered the accuracy is poor and this is due to the inclusion between intervals, the values that are near the maximum value in an interval gave excellent accuracy, giving that the maximum value of each interval can be included in another one, while the maximum value is not.

V. CONCLUSION & FUTURE WORKS

In this paper, we demonstrate that AI techniques can give more accurate results in machine state diagnosing. We propose to generate fastly and smartly FL rules based on Truth Tables. Moreover, we propose to justify choice of membership function by simulation method. In terms of business context, this study has achieved two major goals. The first one is that it proves that it is possible to conserve old FMECA results, and used them as references in real-time diagnostics. the second achievement is combining experts' knowledge with numerical data using AI, which gave more accurate and reliable results, that will minimize the time of all interventions, it will allow the agents to go straight to the source of the problem and solve it, in a short time, fewer resources, and avoid bigger issues that could stop the whole production process. The obtained results show that the trapezoidal membership functions (trapMF) give better results, and better accuracy compared to the other sets, and it can be explained by the fact that it gives a bigger range in which a variable can belong, and it's more realistic and practical for our case. Later, we aim to evaluate the robustness of our model by including more data (metrics and observations) and also comparing it to other models such as FNN (Fuzzy Neural Network). The next step will be machine state prognostic based on the result of the diagnostic step. This will not only the upcoming failure but a detailed machine state.

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N°	fftv	fftg	ExpS ¹	TrapSc ²	TrapS ³	TrapA ⁴	TriSc ⁵	TriS ⁶	TriA ⁷	GaussSc ⁸	GaussS ⁹	GaussA ¹⁰
1	v_{1-min}	g_{1-min}	Nr	0.34	Nr 70% Im 30%	Exc	0.49	Nr 70% Im 30%	Exc	NaN	NaN	Bad
2	v_{1-max}	g_{1-max}	Nr	0.33	Nr 70% Im 30%	Exc	0.40	Nr 60% Im 40%	Exc	NaN	NaN	Bad
3	v_{2-min}	g_{2-min}	Im	2.00	St 100%	Poor	2.06	St 95% Mi 5%	Poor	2.50	St 50% Mi 50%	Good
4	v_{2-max}	g_{2-max}	Im	2.00	St 100%	Poor	2.02	St 100%	Poor	2.5	St 50% Mi 50%	Good
5	v_{3-min}	g_{3-min}	St	2.00	St 100%	Exc	2.06	St 95% Mi 5%	Exc	2.50	St 50% Mi 50%	Good
6	v_{3-max}	g_{3-max}	St	2.03	St 98% Mi 2%	Exc	2.04	St 95% Mi 5%	Exc	2.50	St 50% Mi 50%	Good
7	v_{4-min}	g_{4-min}	Mi	2.46	St 55% Mi 45%	Good	2.00	St 100%	Poor	0.0	Nr 100%	Bad
8	v_{4-max}	g_{4-max}	Mi	2.08	St 90% Mi 10%	Ave	2.07	St 95% Mi 5%	Poor	NaN	NaN	Bad
9	v_{5-min}	g_{5-min}	MI	3.02	Mi 98% MI 2%	Poor	2.38	St 65% Mi 35%	Poor	NaN	NaN	Bad
10	v_{5-max}	g_{5-max}	MI	4.73	BI 75% MI 25%	Ave	4.64	MI 65% BI 35%	Good	0.0	Nr 100%	Bad
11	v_{6-min}	g_{6-min}	Bl	3.96	MI 100%	Poor	3.11	Mi 90% MI 10%	Poor	Nan	NaN	Bad
12	v_{6-max}	g_{6-max}	Bl	4.73	BI 75% MI 25%	Exc	4.59	MI 60% BI 40%	Good	1.76	St 75% Im 25%	Bad
13	v_{7-min}	g_{7-min}	Gf	3.90	MI 90% MI 10%	Poor	2.98	Mi 100%	Poor	NaN	NaN	Bad
14	v_{7-max}	g_{7-max}	Gf	5.66	Gf 70% BI 30%	Exc	5.51	Gf 50% BI 50%	Good	0.0	Nr 100%	Bad

1 State by Experts; 2 Score of Trapezoidal; 3 State of Trapezoidal; 4 Trapezoidal Accuracy; 5 Score of Triangular; 6 State of Triangular; 7 Triangular Accuracy; 8 Score of Gaussian; 9 State of Gaussian; 10 Gaussian Accuracy.

TABLE VI
RESULTS OF THREE FUZZY LOGIC MOTOR

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